The International Journal Of Engineering And Science (IJES)
||Volume|| 2 ||Issue|| 12 || Pages || 48-56 || 2013 ||
ISSN (e): 2319 – 1813 ISSN (p): 2319 – 1805

Using MLP neural networks for predicting global solar radiation

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--ABSTRACT--
The artificial neural networks have attracted the attention in many researchers in the field of renewable energy, especially for the prediction of meteorological data such as solar irradiation. For this reason, we developed a model based on the multilayer perceptron (MLP) neural networks to predict the evolution of solar radiation on a daily scale in the region of Sebt El Guerdane - (Agadir, Morocco). In this study, we used a large database on the meteorological data of 1642 days, collected between 2008 and 2012. This database consists of a number of meteorological parameters such as humidity (Minimal, average and maximum), air temperature (Minimal, average and maximum), precipitation, potential evapotranspiration of reference and wind speed. The test results of the developed model based on the multilayer perceptrons are compared to those obtained with the developed model based on the multiple linear regression method as a classic statistical. The obtained results demonstrate the efficiency of the MLP neural network than the classical statistical method to predict purpose with a high accuracy.

Keywords *- Solar Radiation, Modeling, predicting, ANN, MLP, MLR.*

Date of Submission: 25 December 2013 ⟺ Date of Acceptance: 01 January 2014

I. INTRODUCTION

Solar radiation is one of the most difficult meteorological parameters to estimate because it depends on several climatic, geographical and astronomical parameters. Indeed, the global solar radiation values are the most important parameter for the solar energy applications [1]. In literature, neural networks have found great success in modeling and predicting solar radiation at hourly time scales [2], daily [3;4] or monthly [5;6] and for several localities in the world [7;8].

Artificial Neural Networks (ANN) are analogue computer systems, which are inspired from studies on the human brain and known to be universal approximates [9]. The ANN can obtain the structure of a complex system by repeated network training procedure and describe its property using mathematical equation [10]. ANN has also been used to identify models of complex systems because of their high robustness and ability to learn. The advantage of ANN in respect to other models is its ability of modeling a multivariable and extracting the implicit non-linear relationship among these variables by means of learning with training data [11].

The objective of this work is to use mathematical modeling tool for predicting solar irradiation. For this purpose, we are interested to applied the artificial neural networks method based on the multilayer perceptron (MLP) to find the most effective model to predict the average daily global solar irradiation in the region of El Sebt Guerdane - (Agadir, Morocco).

II. MATERIALS AND METHODS

II.1 Description of the study zone

The Sebt El Guerdan of Agadir region is located in the center of Morocco (Fig. 1). It presents different advantages such as: peaks of the High Atlas Occidental Pre Saharian, cost plain winter, the annual rainfall is low and erratic: 200 mm / year on average in the plains. The temperatures are moderate, the mean annual temperature is about 19°C, the average maximum temperature is 27°C and the minimum is 11° C. In general, the high sunshine (3.000 hours of sunshine per year) and the mild climate make the zone Sebt El Guerdane the first agricultural region of the country. The average annual evaporation varies between 1400 mm in the mountains and close the Atlantic coast, and 2000 mm in the plains [12].

Figure 1: Situation of the study zone

II.2 Data Description

The database used in this work contains ten weather variables values for the zone Sebt El Guerdane - (Agadir, Morocco). It divided in two parts of variables:

- Nine independent variables (explanatory): the humidity rate (average, maximum and Minimum,), the air temperature (Minimal, average and maximum), precipitation, potential evapotranspiration and reference wind speed.
- A dependent variable: solar radiation, which is recording during the period from 01/01/2008 to 14/06/2012.

II.3 Neural networks Model

A formal neuron is a nonlinear algebraic and function bounded whose value depends on the settings called "weight". The values of this function are called "inputs" of the neuron and the obtained values from this function are called the "output". Figure 2 shows a graphic of a formal neuron model representation. The most commonly used Networks are those where the function S is a non linear function, usually a sigmoid function described as:

$$\mathbf{S(Y_i) = \frac{1}{1 + exp(-Y_i)} \quad Where\ Y_i = \sum_{i=1}^{N} W_i\, X_i}$$

Where: S (Y_i): Transfer function;
Y_i: Weighted sum of the inputs;
W_i: Connection weights;
X_i: Input values;

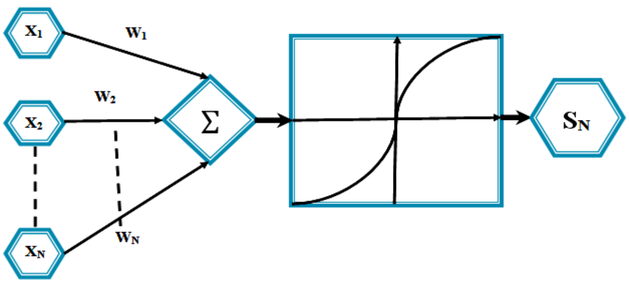

Figure 2: Formal neuron model

II.4 Architecture of the neural network

The figure 3 shows a neural network with a non-buckled structure of multilayer perceptron type. This structure includes inputs, layers of neurons "hidden" and output neurons. The main idea of the MLP is to group neurons in layer. After that we place end to end several layers and connect completely the neurons of the adjacent layers in pairs.

The n layer entries will therefore be the neurons of (n-1) layer outputs. Neurons of the first layer are connected to the outside world and receive the input variables.

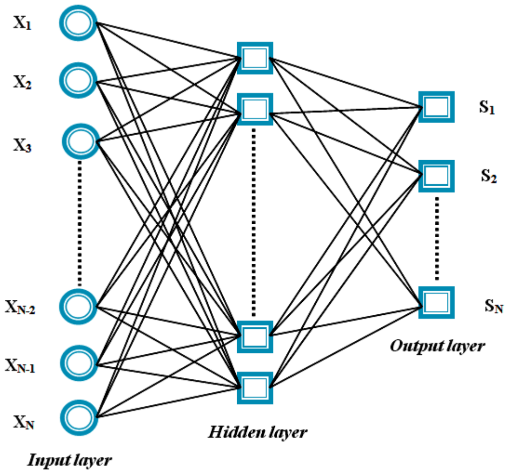

Figure 3: Multilayer Perceptron architecture

To create the optimal structure of the MLP neural network, we conducted several training by varying the network parameters such as the activation function, number of hidden layers, number of neurons in each layer, the learning function, the iteration number and the pitch of training [13;14].

In this study, the two activation functions are used: a sigmoid function in the intermediate layer and a linear function in the output layer. Previous works have shown that this pair of functions can approximate any function of interest with arbitrary precision, provided you have enough neurons in the hidden layer [15].

II.5 formatting of data

The input data (independent variables) are unprocessed raw values. They have very different orders of magnitude depending on the variables. To standardize the measurement scales, these data are converted into standardized variables.

Indeed, the values Xi of each independent variable (Yi) were standardized with respect to its mean and standard deviation according to the relationship:

$$\widehat{X}_i = \frac{X_i - \mu_i}{\sigma_i}$$

$\widehat{X}_i$: Standardized value for the variable i;

X_i : Raw value for the variable i;

μ_i : Average value for the variable i;

σ_i : Relative standard deviation of the variable i.

The corresponding values for the dependent variables were also normalized in the interval [-1, 1] from the relation:

$$\widehat{X}_i = \frac{2(X_i - \mathrm{Min}(X_i))}{(\mathrm{Max}(X_i) - \mathrm{Min}(X_i))} - 1$$

The input (weather parameters) and output (Solar radiation) are normalized a range of [-1;1] to adapt it to the requirements of the transfer function used in this study. To justify the predictive quality of the models, weather data are divided in two groups. The first one corresponds to 70% of the total data, and the second one corresponds to 30% of the total data that have not used as a training data.

III. RESULTS AND DISCUSSION

III.1 MLP neural network

To determine the network architecture to be used, we have varied the number of hidden layers, number of neurons in the hidden layer, transfer functions and training algorithms. Two performance indexes, the correlation coefficient (R) and the mean squared error (MSE), were calculated for to demonstrate the robustness of the developed model.

The correlation coefficient (R) is the total error of the dependent variable y (values of solar radiation) explained by the model. This coefficient is expressed by [16].

$$R = \sqrt{1 - \frac{\sum_{j=1}^{N}(Y_j - Y_{moy})}{\sum_{i=1}^{N}(Y_i - Y_{moy})}}$$

Y_j : The output obtained by the network.
Y_i : The target (the desired output).
Y_{moy} : The average of the measured values of Y_i.
N: The number of samples.

The mean squared error E is defined by the following equation [17]:

$$\mathrm{MSE} = \frac{1}{N}\sum_{i,j=1}^{N}\left(Y_j - Y_i\right)^2$$

The basis of learning and the test database:

According to the calculation of the mean squared error (MSE), we noticed that the best percentage for the basis of training is 70% (Table 1).

Table1: The distribution of the data set.

	MSE 1	MSE 2	MSE 3
Training base : 90% Test base : 10 %	0.00681	0.00610	0.00920
Training base : 80% Test base : 20 %	0.00634	0.00477	0.00482
Training base : 70% Test base : 30 %	**0.00447**	**0 .00447**	**0.00446**

The number of hidden layers:

In Table 2, we present the obtained values of MSE for one, two, three and four hidden layers. We noticed that by increasing the number of hidden layers, the load of calculations increases without any performance layers. So, the obtained values of MSE prove that with a single hidden layer, the developed model gives more precise results than the other number.

Table 2: Performance of the system based on the number of hidden layers

Number of hidden layers	MSE 1	MSE 2	MSE 3
1	**0.00447**	**0.00447**	**0.00446**
2	0.00706	0.00575	0.00560
3	0.00567	0.00455	0.00667
4	0.00674	0.00783	0.00457

Selecting the best activation function:

There are several activation functions, the most important are:

- ✓ The linear activation function.
- ✓ The sigmoid function or the log sigmoid function.
- ✓ The hyperbolic tangent function or bipolar.

Table 3: Activation function in the hidden layer and the output layer.

Hidden layer	Output layer	MSE 1	MSE 2	MSE 3
Sigmoïd	Sigmoïd	0.00591	0.00659	0.00633
Sigmoïd	Linear	**0.00574**	**0.00648**	**0.00494**
Linear	Sigmoïd	0.03480	0.03480	0.03480
Linear	Linear	0.03870	0.03870	0.03870

The obtained results showed that the best combination for the activation functions in the hidden layer and the output layer is: the sigmoid function for the hidden layer and linear function for the output layer (Table 3).

The number of neurons in the hidden layer:

To determine the best number of neurons in the hidden layer, we varied this number between one and twenty. We have found that the best number of neurons in the hidden layer is four neurons (Table 4).

Table 4: Performances of the system based on the number of neurons

Number of neurons in the hidden layer	MSE 1	MSE 2	MSE 3
1	0.03420	0.03420	0.03420
2	0.00947	0.00916	0.03350
3	0.00661	0.00656	0.00939
4	**0.00216**	**0.00227**	**0.00148**
5	0.00500	0.00418	0.00440
6	0.00548	0.00448	0.00388
7	0.00386	0.00364	0.00412
8	0.00367	0.00529	0.00404
9	0.00341	0.00322	0.00306
10	0.00322	0.00300	0.00325
11	0 .00388	0 .00260	0.00288
12	0.00267	0.00287	0.00303
13	0.00287	0.00294	0.00253
14	0.00242	0.00315	0.00224
15	0.00249	0.00284	0.00282
16	0.00318	0.00248	0.00247
17	0.00543	0.00228	0.00193
18	0.00900	0.00247	0.00282
19	0.00516	0.00427	0.00548
20	0.00252	0.00239	0.00227

Selecting the optimum training algorithm:

The identification of neural network MLP requires two steps [18;19]:

- ✓ The first step is to determine the structure of the network; different networks with one hidden layer were tried.
- ✓ The second step is to identify the parameters (Training neural networks).

In this study, we used different training algorithms, which are referred as a high performance:

- Gradient descent backpropagation (GD).
- Gradient Descent with Adaptive training rule backpropagation (GDA).
- Gradient descent with momentum backpropagation (GDM).
- Gradient descent with momentum and adaptive training rule backpropagation (GDX).
- Levenberg Marquardt (LM).

The obtained values of the mean squared error (MSE) and training parameters (η, α) are presented in Table 5.

From this table we conclude that the Levenberg-Marquardt algorithm gives the minimum mean squared errors. Furthermore, the figure 4 shows the evolution of the squared error of the training depending of the number of iterations. We note that the error is very small and after the eighth iterations, the network is stable with a minimum mean square error less than 0.0647. Beyond this value, it is necessary to stop training for a number of iterations equal to 30 optimal iterations. This phase allowed us to determine the optimal structure of the first neural network.

Table 5: Performances of the system based on various algorithms

Algorithm	Parameters / Values		MSE 1	MSE 2	MSE 3
	η				
GD	0.01		0.160	0.282	0.317
	0.10		0.324	0.309	0.297
GDA	0.01		0.257	0.163	0.213
	0.10		0.147	0.199	0.170
	η	α			
GDM	0.01	0.9	0.242	0.184	0.199
	0.10	0.9	0.228	0.190	0.150
	0.01	0.3	0.417	0.268	0.202
	0.10	0.3	0.235	0.173	0.167
	0.01	0.6	0.249	0.171	0.264
	0.10	0.6	0.201	0.236	0.205
GDX	0.01	0.9	0.177	0.168	0.217
	0.10	0.9	0.188	0.239	0.154
	0.01	0.3	0.204	0.178	0.264
	0.10	0.3	0.174	0.222	0.174
	0.01	0.6	0.237	0.137	0.326
	0.10	0.6	0.169	0.214	0.170
LM	η = 0.001		0.00647	0.00647	0.00695

Where **η** : Training rate; α : Momentum.

The network has been driven to reach the stage of overtraining, this has been met after 30 iterations, it is interesting to continue learning until you reach this stage for the test in order to reduce the gradient more and therefore improve our network (Figure 5). From the obtained results in Figure 5 we note the different values of training parameters founded in this study:

Training parameters are as follows:

- Maximum number of iterations (epochs) = 30.
- Training rate (η) = 0.001.
- Minimum gradient = 0.00025.

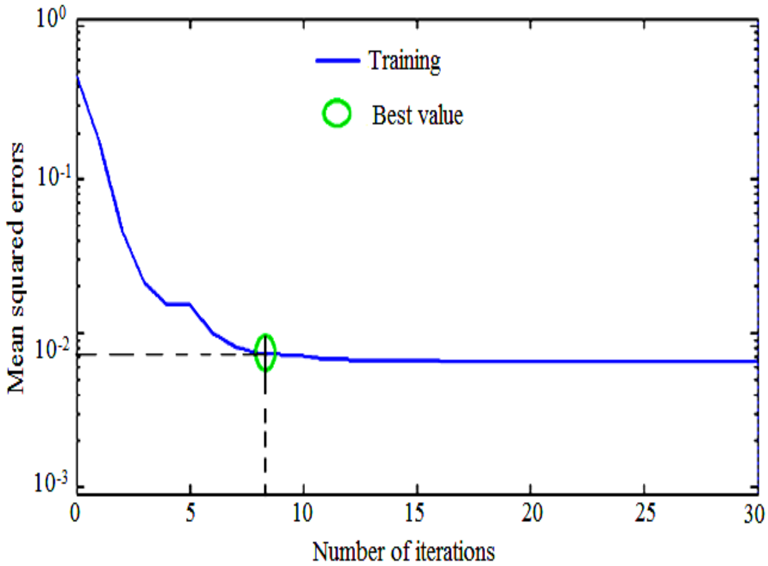

Figure 4: Evolution of the mean squared error for a network architecture [9-4-1].

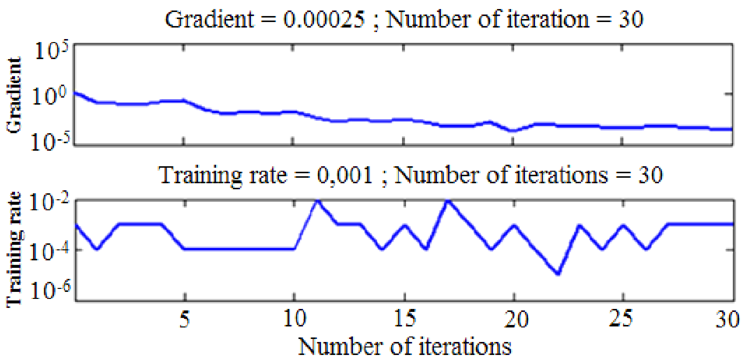

Figure 5: Variations gradient of the error, the training rate and the validation error based on number of iterations.

Among the various network configurations tested, we choose that producing the lowest mean squared error on the entire database.

From the obtained results, the architecture of the developed MLP neural network model is [9-4-1] to predict solar irradiation (Fig. 6). To more improve the effectiveness of the developed model, in figure 7 we draft the scattering diagram of measured and predicted data.

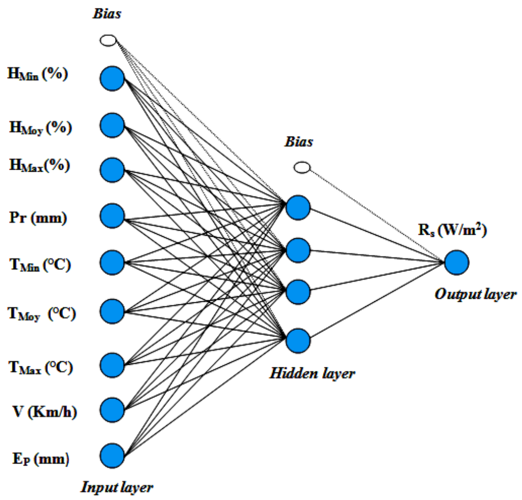

Figure 6: Architecture of MLP the neural network with three layers configuration [9-4-1] used in this study

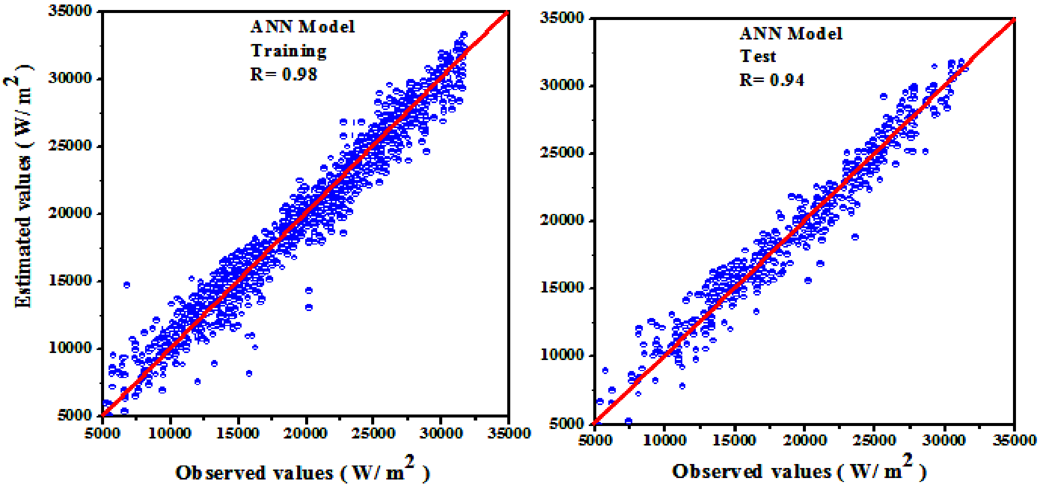

Figure 7: Scattering diagram by MLP neural networks measured and predicted data for training and testing phases

For the MLP neural networks models, the correlation coefficients almost equal to one (R^2~1), this shows that there is a greater approximation between the measured values and those estimated by the developed neural network model. This model can be considered as a highly effective tool in the field of the study of weather forecasting in general and especially the solar irradiation.

III.2 Multiple linear regression model (MLR)

Multiple linear regression is a data exploration method to study the relationship and dependence between a dependent and independent variables. The equation of the developed model in this study is as described as follows:

$$\mathbf{R_s}\ (\mathbf{W/m^2}) = -8419.56 - 26.07 * \mathbf{H_{min}} + 22.68 * \mathbf{H_{moy}} + 148.43 * \mathbf{H_{max}} - 79.01 * Pr + 44{,}79 * \mathbf{T_{min}} - 469.38 * \mathbf{T_{moy}} + 162.25 * \mathbf{T_{max}} + 158.98\ \mathbf{V} + 3832.44 * \mathbf{Ep}$$

With:

- H_{min}: Minimum moisture;
- H_{moy}: Average moisture;
- H_{max}: Maximum moisture;
- T_{moy}: Average temperature;
- T_{min}: Minimum temperature;
- ***V:*** Wind speed;
- T_{max}: Maximum temperature;
- ***Ep:*** Potential evapotranspiration;
- ***Pr:*** Precipitation;
- R_s: Solar radiation.

The solar radiation calculated from this equation is shown in Figure 8.

The coefficient of correlation obtained by the regression model for the series of training was 81% and 84% for testing. This shows that the parameters studied are non-linear.

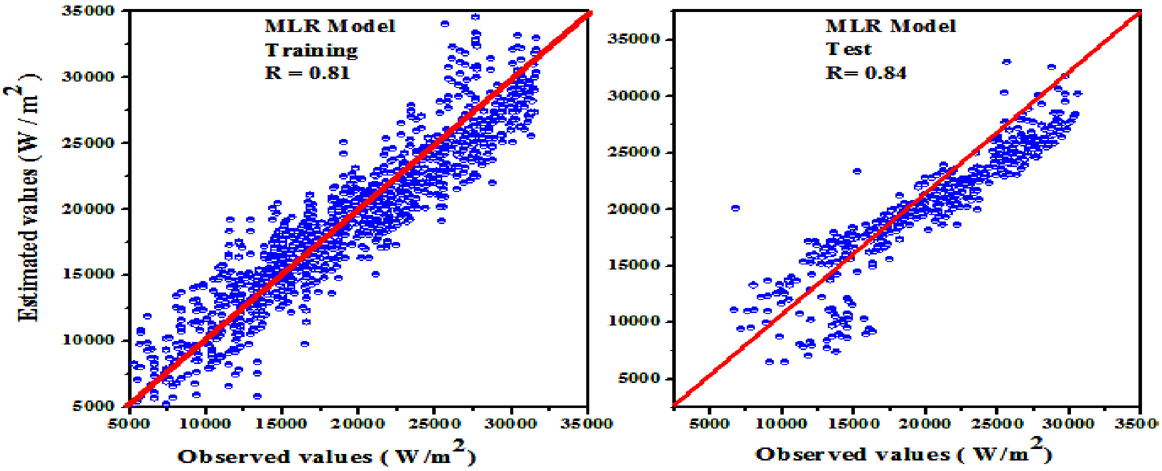

Figure 8: Scattering diagram of measured and predicted data by regression model for training and testing phase.

From the figures 7 and 8, it can be concluded that the estimated values by the established models by the neural networks are much closer to the observed values, against those obtained by the models established by the multiple linear regression are widely further observed values. These results demonstrate the advantages of the MLP models, where we note a very good correlation between simulated and observed values with a very good correlation coefficient. This proves the predictive power of these models established by neural networks in predicting the solar radiation from meteorological parameters. The obtained results from the models developed by ANN proved its accuracy, since they are very close to the actual measurements. We can see that the validity of the models on the basis of training is essentially the same in both cases, R = 0.98 for ANN against R = 0.81 for the MLR (Table 6).

Table 6: Values of the correlation coefficients

	Neural Network	Multi Linear Regression
R: Training phase	0.98	0.81
R: Testing phase	0.94	0.84

Neural networks nonlinearity is taken into account using the non-linear transfer function. The degree of complexity can be controlled by varying the number of nodes in the hidden layer. So, the artificial neural networks thus appear as a valuable tool in the field of meteorological forecasting. Finally we concluded that neural networks possess a large capacity for training and predicting solar radiation time series compared to those established by the MLR models.

IV. CONCLUSION

In this study, we are interested to develop a model based on the MLP neural networks to demonstrate that solar radiation is a variable that does not act alone but it has explained by other meteorological variables with non-linear relations. The obtained results demonstrate the advantages of MLP neural networks on linear regression models.

This study confirms the ability of the neural networks to predict solar irradiation accurately in the absence of measurement. The obtained results indicate that modeling neural networks seem promising for evaluating the potential of the solar resource in the region of Sebt-EL Guerdane.

As a perspective to this study, we intend to predict solar irradiation at smaller scales temporary (day, hour, minute) if a suitable database is available, and to work on other types of neural network: radial network function, network competition and genetic algorithms,

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